Provider Networks and Primary Care Signups: Do They Restrict the Use of Medical Services?*

Partha Deb†
Department of Economics
Hunter College, City University of New York

Pravin K. Trivedi
Department of Economics
Indiana University

March, 2004

Abstract

This article analyzes the effect of gatekeeper and network restrictions on use of health care services. Simulation-based methods are used to jointly model the choice of gatekeeper and network attributes of health insurance plans and health care utilization respecting the multinomial nature of health plan choice, the discreteness of utilization, and the possibility of self-selection into insurance plans. Using data from the Community Tracking Survey (1996-1997), we find significant evidence of selection into plans with gatekeeper and/or network restrictions. Enrollees in plans with networks of physicians have fewer office-based visits to non-physician medical professionals, but more emergency room visits and hospital stays. Individuals in plans that require signups with a PCP have more visits to non-physician providers of care, more surgeries and hospital stays but substantially fewer emergency room visits. Enrollees of plans that do not pay for out-of-network services have more office-based and emergency room visits, but less surgeries and hospitalizations.

Keywords: Community Tracking Study; Maximum Simulated Likelihood; Self-selection; Plan Attributes

---

*This research was funded by a grant from the Robert Wood Johnson Foundation (#044192). We thank Chenghui Li for excellent research assistance and Jim Reschovsky for detailed comments. We also thank seminar participants at Rutgers University for their suggestions.

†Corresponding author: Department of Economics, Hunter College, 695 Park Avenue, 1524W, New York, NY 10021. Email: partha.deb@hunter.cuny.edu, Phone: 212-772-5435, Fax: 212-772-5398.

1. Introduction

In this paper, we examine the effects of gatekeeping and network attributes of health insurance plans on the use of various categories of health care services. The econometric model we develop takes into account possible effects of self-selection into such plans.

Historically, the market for health insurance consisted mostly of indemnity plans that paid some fraction of the fees charged by providers for medical services. Such plans, typically known as fee-for-service (FFS) plans, varied mostly along financial dimensions: deductibles, copayments, and caps on out-of-pocket expenditures, but sometimes also varied in the types of services covered and the limits on coverage for some services (e.g., preventive care, prenatal care, mental health care). Generally, there were few or no restrictions on the providers covered under the plans. With the emergence and growth of Health Maintenance Organizations (HMOs) and other types of managed care organizations (MCOs) that combine insurance for and provision of health care, this traditional view of the market has become less important. Managed care plans, in general, and HMO's in particular, place significant restrictions on provider choices and the process of care. Hence, health plan choice is no longer simply a matter of selecting a system for financing medical care, but instead involves choosing a set of providers and system for delivering care. In recent years, the distinction between HMO and non-HMO managed care plans has also become increasingly ambiguous and traditional FFS plans virtually extinct. All types of health insurance plans, including most FFS plans, place restrictions on types and amounts of care and generally manage the process of medical care (Gold et al. 1995; Pauly and Nicholson, 1999). Moreover, less restrictive forms of HMOs have gained market share, muddying the distinctions further.

While there is a large literature on the effects of managed care organizations (MCOs) on the utilization of care (for reviews, see Glied, 2000; Miller and Luft, 1994) using broad labels such as HMO, PPO, POS and FFS, there is very little evidence on the specific effects of gatekeeping and/or network restrictions of MCOs on the utilization of services. An understanding of the effects of such substantive gatekeeping and network attributes of plans on the use of health care are clearly important for public policy and plan-design reasons. This is the issue we address in this study. We use data from the Community Tracking Study, a large nationally representative study that provides such health-plan information, and develop an econometric methodology that addresses issues raised by the endogeneity and multinomial nature of classification of insurance plans, and the count data nature of measures of utilization of health care services. To our knowledge, this is the first study to conduct such a comprehensive analysis in a national context.

There is relatively little empirical literature on the effects of gatekeeper and network restrictions of MCOs on the use of health care services. Feldman, et al. (1989) estimate a nested logit model of health plan choices in which the nest is defined by whether or not the plan has any restrictions on provider choice. The focus of the study is on price sensitivity; price is found to be an important predictor of health plan choice, and that enrollees in plans with restrictions on provider choices appear to be more sensitive than FFS enrollees to employee contributions. Escarce, et al. (2002) use administrative data to compare medical expenditures between enrollees in an HMO that does not pay for out-of-network services with a POS plan that does. Both plans require signups with a primary care provider (PCP). They find that expenditures of enrollees in the POS plan are no larger than those of enrollees in the HMO plan, even though it covers (partially) care received outside the network of providers. Finally, Kemper, et al. (2002) use data from the Community Tracking Study to examine the effects of plan design on utilization and satisfaction with care. Although their definitions of plan-types begin with information on attributes, they do not report results for the effects of specific attributes on utilization. Instead, they report results for bundles of attributes defined on a scale from least to most restrictive. They find that physician and non-physician medical practitioner visits increase along the continuum from indemnity plans to group/staff model HMOs. They find no differences in utilization of hospitals, surgeries and emergency rooms between plan-types.

The literature on the effects of MCOs on utilization varies considerably in the treatment of self-selection into health insurance plans. Among recent studies, Goldman (1995), Cardon and Hendel (2001) and Mello, et al. (2002) explicitly address the issues. Goldman and Mello, et al. also find considerable evidence of self-selection. But a great deal of other work either assumes that the self-selection effect is negligible (see references in Glied, 2000, and Miller and Luft, 1994), or gives reasons why the impact might be small (Christensen and Shinogle, 1997; Tu, Kemper and Wong, 1999). In the small literature examining attributes of plans, Escarce, et al. (2002) model but find no evidence of selection between the two plans, while Kemper, et al. (2002) do not model self-selection.

In this paper, we develop an econometric approach to estimate the effects of restrictions on provider access and choices (defined along three dimensions) on the use of health care services. Although in theory plans could bundle any combination of attributes, in practice they tend to consist of a relatively small number of distinct bundles. For example, when providers belong to a group/staff model HMO or are paid by capitation, then enrollees are almost always required to sign up with a PCP who is often at financial risk and acts as the gatekeeper to care from specialists. Further, visits to providers outside the network are discouraged by financial penalties. Considerations of administrative efficiency may encourage the plans to use only few restrictions bundled together. Such bundling reduces the desirable independent statistical variation in the occurrence of attributes in plans and thereby makes it difficult, if not impossible, to directly model the impact of restrictions on use, an issue also considered by Kemper, et al. (2002). Our modeling strategy is to begin by modeling the choice of one out of several bundles of restrictions using a traditional multinomial choice models (Amemiya, 1985; Train, 2002); but subsequently we take a hedonic approach (Gorman, 1980; Lancaster, 1966) and provide a method for backing out the implied effects of each of the three restrictions on provider access and choice on utilization. Our econometric methodology also allows for possible endogeneity of health plan choice induced by self-selection, the discreteness of measures of utilization, and the multinomial nature of the plan-bundles.

In such models, instrumental variables methods (linear and nonlinear) are either inappropriate or have poor finite sample properties because they ignore discreteness of treatment and outcome, relationships between treatment indicators (multinomial), and involve linear approximations of highly nonlinear functions. Consequently, we apply maximum simulated likelihood (MSL) techniques to estimate the parameters of our models. Simulation is used to evaluate integral expressions in the likelihood function of the model as no closed form solutions exist.

The remainder of this paper is organized as follows. Section 2 presents the econometric modeling framework that describes the mechanisms by which selection into plans operates and how that affects health care utilization. Section 3 describes the econometric framework. The data are described in Section 4. Section 5 presents and discusses the empirical results. Section 6 concludes.

2. Conceptual Framework

Several economic models have been developed in the literature to explain the consumer's choice of a health insurance plan and its relationship to the subsequent use of health care services (e.g., Cameron et al., 1988). In the standard model a consumer maximizes expected utility

$$\max_{\{d_j, C, \mathbf{y}\}} \mathrm{EU}_j = \int U\left(C, H\left(\mathbf{y}, s|\mathbf{A}, d_j\right) d\pi(s|\mathbf{A})\right) \qquad j = 1, ..., J, \tag{1}$$

where C denotes consumption of other goods, H denotes a "health production function", $\mathbf{y}$ denotes the vector of health care services, s denotes a random state of health whose subjective probability distribution obeys the probability law $\pi(s|\mathbf{A})$, $\mathbf{X}$ is a vector of individual characteristics, both observed and unobserved and d_j is the health plan chosen from a set of J mutually exclusive alternatives subject to the constraint

$$C(s) + p_j \mathbf{y}\,(s) = M - P_j, \tag{2}$$

where p_j is the vector of net real out-of-pocket prices of health care services resulting from the choice of insurance plan j and M is income.

In a model with focus on the role of attributes, the discrete plan choice variable d_j is expressed as a function of m attributes or features, $d_j = f_j\left(g_j\left(z_1, ..., z_m\right)\right)$. Here the inner function $g_j\left(z_1, ..., z_m\right)$ is a transformation from the attribute space to the characteristics space, characteristics being such properties as convenience, ease of access, breadth of choice and so forth. Such characteristics of plans are generated by the combination of attributes. If the characteristics are essentially the same as attributes then transformation from attributes to characteristics is said to be the identity transformation. The outer function $f_j\left(g_j(\cdot)\right)$ is a transformation from the characteristic space to the goods space. That is, each good is a bundle of characteristics. Utility depends upon the characteristics which are "consumed" through the purchase of goods. The economic basis of the attribute-based model is the so-called Gorman-Lancaster characteristics approach (Lancaster, 1966; Gorman, 1980) to demand analysis.

In the Gorman-Lancaster approach different goods (here plans) are differentiated in terms of the specific attributes that they bundle and the quantities in which they bundle them. Different combinations of the attributes generate the characteristics of the goods, and the consumers derive utility from the characteristics of the goods rather than from the goods themselves. Therefore, consumer preferences are defined over the space of the characteristics or the attributes of the goods. These attributes may be continuously or discretely measurable, and they may represent desirable or undesirable features. For example, each insurance plan can be viewed as a specific bundle of attributes, and differences between plans reflect the different combinations of attributes, selected from a larger set of such attributes, embodied in each plan. The existence of a list of preferred providers is one such attribute of a plan. Whether or not a referral is required for specialist care is another such attribute. Hence the utility derived from different types of insurance plans is ultimately derived from the attributes of those plans, or from the combination of such attributes, such as the imposition or absence of restrictions that they place on access to and the use of health services. A household, typically consisting of more than just one member, places a utility value on the characteristics of a plan in a manner that reflects individual or collective preferences. The collective presence or absence of attributes, i.e., the bundled attributes, defines the plan.

The consumer's allocation problem is restated as that of maximizing expected utility

$$\max_{\{\mathbf{z},C,\mathbf{y}\}} \mathrm{EU}_j = \int U\left(C, H\left(\mathbf{y}, s|\mathbf{A}, d_j\left(\mathbf{z}\right)\right) d\pi(s|\mathbf{A})\right) \ , \tag{3}$$

where $\mathbf{z}$ is the vector of plan attributes. In practice, because attributes are not directly bought and sold, consumer preferences on $\mathbf{z}$ are expressed through preferences on bundles of attributes.

A basic feature of these models is that they lead to interdependence between the choice of plan and the subsequent demand for health care. Having a health insurance plan changes both the relative price of health care services and the net disposable income of the household, and thereby impacts on the demand for care; but the choice of insurance itself depends in part on anticipated use of health care services, which in turn is a function of health status of individuals, attitude to health risks, and various socio-demographic factors such as age, sex, marital status and so forth. Not all the relevant factors are observable, so unobserved interindividual differences play a role both in the choice of insurance plan and in the determination of health care use after enrollment into the plan. These arguments imply that statistically the health insurance status in the utilization model is endogenous, not exogenous or pre-determined.

Self-selection into plans also creates interdependence. In our model self-selection occurs because optimizing individuals, possessing knowledge of their own health attributes, proclivities, and economic constraints, select plans accordingly. Self-perceived healthy individuals, expecting lower demand for future health care, may choose low-cost plans with fewer choices than their less healthy counterparts. Others may have preferences for certain modes of care, e.g., office-based care from their family physician, and hence may choose plans with generous benefits in those dimensions. Therefore these attributes which partly determine the individual's choice of health plans also affect their expected utilization of services.

Figure 1, following Walker and Ben-Akiva (2002), summarizes the conceptual framework in a schematic form. It indicates distinctions between measurement, structural and stochastic relationships between and among attributes, plans and utilization.

3. Econometric Strategies

Generally, three approaches are commonly adopted in models of relationships between treatments and outcomes in observational data to handle the complication of endogeneity and self-selection: 1. instrumental variables; 2. control functions; 3. full parametric specification of outcome and treatment equations. In this paper we use a blend of the third and first approaches.

As is well-known, in the instrumental variable (IV) approach the outcome equation is estimated after specifying instruments, denoted $\mathbf{W}$, defined as variables that are correlated with treatments, but uncorrelated with the outcomes, conditional on other exogenous variables. That is, valid instruments are those that impact on outcomes solely through the treatment variables. Such instruments, being capable of generating independent movements in the treatment variable are considered causal determinants of the treatment variable and hence potentially can identify an average impact parameter. Let ε denote the random or unpredictable component of health care use. Existence of valid instruments then implies that the moment condition $\mathrm{E}[\boldsymbol{\varepsilon}|\mathbf{W}, \mathbf{A}] = 0$, is satisfied and consistent estimation of the outcome equation is possible.

The control function (CF) methodology is similar to the to the IV approach. Here one seeks variables or estimated functions of observable variables, denoted $c(\boldsymbol{\varphi})$, such that the moment condition $\mathrm{E}[\boldsymbol{\varepsilon}|\mathbf{c}(\boldsymbol{\varphi}), \mathbf{A}] = 0$ is satisfied. In one variant of this approach additional variables that are good independent predictors of the treatment variables are added to the regression function and then the regression estimated by a least squares type procedure. In another variant of this approach a residual from a reduced form equation for the treatment variable is added in the outcome equation regression function. The CF approach is closely related to the IV methodology, especially for the linear outcome and treatment equations (Vella and Verbeek, 1999).

Important advantages of IV, especially in the context of linear models, are well documented (see Angrist, 2001). Under appropriate conditions they include consistent estimation, computational simplicity, and an absence of strong distributional assumptions. For nonlinear and limited dependent variable models, the advantages of the IV/CF methods are less well understood (Angrist, 2001; section 2). First, efficient estimation is computationally awakward because optimal nonlinear instruments are hard to find (Amemiya, 1985). Second, in the context of this paper where the outcome variables are counts, usually with a high proportion of zero-valued outcomes and where treatment is a multinomial set of dummy variables, IV/CF procedures, being "distribution-free", usually provide a poor fit to the data relative to parametric nonlinear models.

Consequently, we use a fully parametric approach in which we specify a set of insurance-plan choice equations, an outcome equation, and the latent relationship between treatment and outcome equations. We use a set of "instrumental" variables to "identify" our structure, i.e., our model incorporates exclusion restrictions. These are defined in the next section. Econometric details of our approach, which requires parametric specification of functional forms of regression functions, error terms and latent variables, are given in section 5.

4. Data

Data for this analysis come from two linked surveys conducted as part of the Community Tracking Study, henceforth referred to as the CTS (Center for Studying Health System Change, 2000). The CTS, sponsored by the Robert Wood Johnson Foundation, is a national study designed to provide information about changes in the health care system and the effects of these changes on care delivery on individuals. One component of this study is the CTS Household Survey, a large, nationally representative survey of more than 60,000 individuals. We use data collected in 1996–1997. A total of 60 sites, 51 in metropolitan areas and 9 in nonmetropolitan areas, were randomly selected to form the core of the CTS. The Household Survey (HS) was administered to households in the 60 CTS sites and to a supplemental national sample of households. Among many other demographic and health care–related items, survey respondents were asked specific questions about restrictions of their health insurance plans. Information was collected also that allowed identification of the insurer and of the product line that covered privately insured respondents. With this information, insurers were contacted and asked to respond to the CTS Insurance Followback Survey (FS), a short questionnaire concerning attributes of the health insurance product. Proxy respondents (e.g., employers) were used when information could not be obtained from insurers. Information from this survey was then matched to household survey respondents to describe their insurance coverage.

We report model estimates based on the sample of individuals with health insurance for whom we are able to match HS and FS data and who are employees of firms. Our choice is motivated by two reasons. We have chosen to use the sample of matched individuals to enable us to use plan characteristics based on insurer responses, which are substantially more reliable. Cunningham, Denk, and Sinclair (2001) report that 25% of individuals misreport whether or not they are in an HMO and that discrepancies between enrollee and insurers reports of health plan restrictions are similar to those for reporting of HMO status. More generally, there is evidence that many consumers are misinformed about the characteristics of the plans they choose (Lubalin and Harris-Kojetin, 1999). Second, to maintain homogeneity in the choice sets of the households, we have used data on only those individuals who are employees of firms. We do not know whether or not an individual was actually offered plans with and without each of the restrictions. It is quite likely that unemployed and self-employed individuals have systematically different choice sets than those who are employees of firms, but that choice sets of employees of firms are much more homogeneous.[1]

[1] Restricting our attention to just employees might be overly conservative as we know that some individuals who are not employees have access to employee insurance plans through their spouses or parents.

Our sample consists of non-elderly adults (ages 18 to 64) who are covered by exactly one private health insurance plan. This includes people who obtain their insurance through an employer, union or professional organization, as well as those who purchase nongroup, individual coverage. The HS contains information on 28,087 such adults. Matched information from the FS was available in the case of 20,786 individuals. Of these, 14,885 individuals are employeed by firms; this is our sample size.

4.1. Restrictions on Provider Choices

Questions about three types of restrictions on provider access and choices were asked of all respondents in the Household and the Followback Surveys. The first restriction is whether plans require enrollees to choose from a list or network of providers (NETWORK). This is based on the survey question - *Is there a book, directory, or list of doctors associated with the plan / this product* ?. The second restriction is whether plans require enrollees to sign up with a PCP (PCPSIGNUP). This is based on the survey question - *Does your plan / product require you to sign up with a certain primary care doctor, a group of doctors, or clinic, which you must go to for all your routine care*?. The third restriction is whether the plan does not cover any of the costs for care received outside the network (NOOUTNET) and is based on the survey question - *If you do not have a referral, will your plan pay for any of the costs of visits to doctors who are not associated with the plan / Under the product, if enrollees do not have a referral and go to out-of-network doctors, does the plan cover any of the costs for these visits* ? Note that a response of "yes" to this question indicates a less restrictive plan. However, for consistency with the other two attributes for which responses in the affirmative indicate restrictive plans, in our empirical analysis we code NOOUTNET=1 or "yes" if the plan does not cover costs associated with out-of-network care.

Table 1 presents frequencies of restrictions as reported by insurers. Most plans have a provider network, almost half require enrollees to sign up with a PCP while over a third of health plans do not pay for care received outside the network. These three restrictions on provider choice form eight mutually exclusive and exhaustive possible bundles of attributes of which five are observed in the data. Table 2 shows frequencies of bundles by sample definition, again as reported by insurers. Let $r_m = (0, 1)$, $m = 1$ (NETWORK), 2 (PCSSIGNUP), 3 (NOOUTNET), denote the absence (0) or presence (1) of restriction m. We label bundles of plans with the notation $B(r_1, r_2, r_3)$, e.g., $B(1, 0, 0)$ means that the first restriction applies to the chosen bundle but the second and third restrictions do not. 11-12 percent of individuals with health insurance are in plans with no restrictions, i.e., plans labeled $B(0, 0, 0)$. These are most likely FFS plans. Insurers report that 35-36 percent of enrollees are in health plans with a network of providers but that do not require a signup with a PCP and pay for out-of-network services. These are labeled as $B(1, 0, 0)$: most PPO plans are likely to be in this bundle. Most POS plans are likely to be characterized by $B(1, 1, 0)$, defined as plans with physician networks and PCP signup requirements but that do pay for out-of-network services. Such plans enroll about 15 percent of the insured. The largest fraction of insured individuals, 33-35 percent, belong to plans with networks and PCP signup requirements and who do not pay for out-of-network services. Such plans, labeled $B(1, 1, 1)$, likely include most closed model HMO's. Finally, about 3 percent of individuals are plans with networks of providers that do not require PCP signups but do not pay for out-of-network services. These plans, labeled $B(1, 0, 1)$, are not easily categorized using standard labels. Differences between frequencies of restrictions and bundles in the sample of all insured as compared to the sample of insured who are employees of firms are generally quite small.

4.2. Outcomes

Our empirical analysis is based on five count measures of health care utilization: visits to an MD, visits to a non-MD medical professional, number of surgeries, visits to an emergency room, and number of hospital stays, all measured over the 12 months prior to the survey. Summary statistics for utilization are presented in Table 3.

4.3. Covariates

The CTS contains detailed information on demographic characteristics, social economic variables, health utilization, health status, and employment of individuals. The covariates we use are defined in Table 4, where we also provide basic summary statistics for the samples of all individuals as well as those who are employees of firms. Demographic characteristics include age (AGE), gender (FEMALE), minority group (HISPANIC, BLACK), years of education (EDUC), family size (FAMSIZE), marital status (MARRIED), and income (INCOME).[2] Employees of firms are somewhat younger, on average, than all individuals with health insurance.[3] They are also slightly less likely to be female. Otherwise, there are no statistically significant differences in demographic characteristics in the two samples.

Health status is captured through two health indices, denoted PHYSCLHLTH and MENTALHLTH, that are measures of general physical and mental health, respectively. Both are scores based on the SF-12 scale which takes into account self-reported health status as well as responses to a list of physical limitation questions. We find that enrollees of health insurance plans who are employees of firms have better physical health, on average, than all individuals with health insurance. This is not surprising given one expects that some individuals are not working because of exceptionally poor physical health. The average mental health in the two groups is, on the other hand, not different between employees and all individuals.

4.4. Instruments and Identification

Issues of model identification arise due to the introduction of endogenous insurance dummies. The model is formally identified by its functional form, but for more robust identification we use the traditional approach of exclusion restrictions or instrumental

[2] Unlike some other work using data from the CTS (e.g., Kemper, et al., 2002; Reschovsky, et al., 2002), we do not include subjective preferences for risk or stated willingness to trade-off costs for provider choice because they are unlikely to be exogenous in models of revealed health plan choices or health care utilization.

[3] Note that both samples are defined for the 18-64 age group.

variables. Therefore, we need to find variables in the dataset that are correlated with the choice of health plan but are, conditional on exogenous variables in the outcome equation, uncorrelated with the outcomes. We use characteristics of the place of employment as identifying instruments in a sample of individuals who all have some form of private health insurance and who are employees of firms. Specifically, the instruments include whether the individual works for the government (GOVTJOB), the size of the firm (FIRMSIZE) and whether the firm offers HMO and non-HMO insurance plans (HMOOFR and NONHMOOFR).

It is important to note that the validity of our instruments are conditional on two sample considerations: 1. every person is enrolled in some form of insurance plan; and 2. every person is an employee of a firm. In so doing, we do not have to be concerned about the implications of the evidence that employment status and whether or not an individual has private health insurance are jointly determined (Gruber, 2000). Everyone in our sample has already chosen to work at a firm, and everyone in our sample has already chosen to be enrolled in a health insurance plan. Thus, employment characteristics such as types of plans offered and the size of the firm serve as proxies for plan supply, which presumably determines the type of plan an individual chooses, but should have no direct relationship with utilization of medical services. Johnson and Crystal (2000) and Olson (2002) also use employment characteristics as instruments in similar contexts.

5. Econometric Model

In this section, we describe our econometric model. We begin by describing our approach to modeling gatekeeper and network attributes of health plans (treatments).

The main objective of the econometric model is to uncover the effects of plan restrictions on the utilization of health care services. In order to model plan restrictions directly, one could estimate individual binary choice models for each of the three restrictions separately. However, because it is not possible to purchase each restriction separately, rather they are available as bundles of restrictions, such separate models are misspecified. In purely statistical terms, the relationships between restrictions manifest as the restrictions having strong associations with each other. In general, such correlations could be incorporated into the model by using a multivariate probit structure but, because only five of the eight possible combinations of restrictions are actually present in the data, estimation of the multivariate probit model is infeasible.[4] Instead, we model bundles of restrictions based on combinations of NETWORK, PCPSIGNUP and NOOUTNET, and we use five such plans in our econometric model. Let $r_m = (0,1)$, $m = 1$ (NETWORK), 2 (PCSSIGNUP), 3 (NOOUTNET), denote the absence (0) or presence (1) of restriction m in plan d_j. Let $B_j = B(r_1, r_2, r_3)$ denote the mapping from plan restrictions to bundles. Thus $B(1,0,0)$ means that the first restriction applies to the chosen bundle but the second and third restrictions do not. Let EV_j^* denote the (latent) indirect utility associated with the j^{th} plan bundle and d_j be binary variables representing the observed choices. Then the indirect utility or propensity to select insurance plan j is formulated as

$$\mathrm{EV}_{ji}^* = \mathbf{z}_i'\boldsymbol{\alpha}_j + \delta_{aj}a_i + \delta_{hj}h_i + \delta_p p_{ji} + \eta_{ji}. \tag{4}$$

where $\mathbf{z}_i$ denotes observed individual-specific (but not choice-specific) socioeconomic characteristics with choice specific parameters $\boldsymbol{\alpha}_j$, a_i denotes unobserved attitudes towards health risks and h_i unobserved components of health status, both individual-specific, with associated parameters δ_{aj} and δ_{hj} respectively. In addition, propensities depend on out-of-pocket prices, p_{ji}, which vary by plan and individual (but are not observed in our data for all possible choices). The η_{ji} are idiosyncratic error terms assumed to follow independent extreme value distributions so that

$$\Pr[d_{ji} = 1|\mathbf{z}_i, a_i, h_i, p_{ji}] = \frac{\exp(\mathbf{z}_i'\boldsymbol{\alpha}_j + \delta_{aj}a_i + \delta_{hj}h_i + \delta_p p_{ji}).}{\sum_{k=0}^{J}\exp(\mathbf{z}_i'\boldsymbol{\alpha}_k + \delta_{ak}a_i + \delta_{hk}h_i + \delta_p p_{ki})} \equiv \mathbf{f}(.) \tag{5}$$

which is the multinomial logit model.[5]

[4] Kemper, et al. (2002) also report on the difficulties of modeling attributes of health plans directly.

[5] Note that, though correlations between bundles are ruled out, correlations between attributes are naturally built in to the multinomial logit model.

The dataset does not have information on the choice sets available to individuals, so we are forced to assume that each individual has each type of plan available to choose from. We recognize that some individuals work for employers who do not offer any choice of health plans and that, although many plans can be purchased in the individual market these may be unaffordable. The statistical justification of assuming that all individuals have the same choice set is that, for each individual, the probability of choosing each of the three types of health plans is necessarily positive, but note that they can be arbitrarily small so as to closely approximate non-availability.

We now describe the model for outcomes conditional on treatment, i.e., these are models of utilization of medical services with dummy variables for plan bundles as endogenous regressors. Let y_i^* denote the value of the latent variable underlying the observed values of utilization, y_i. The outcome or utilization equation is formulated as

$$y_i^* = \mathbf{x}_i'\boldsymbol{\beta} + \sum\nolimits_{j=1}^{4} \gamma_j d_{ji} + \sum\nolimits_{j=1}^{4} \{\lambda_{aj} a_i + \lambda_{hj} h_i + \lambda_p p_{ji}\} + \varepsilon_i \tag{6}$$

where $\mathbf{x}_i$ consist of observed socioeconomic characteristics and a_i, h_i and p_{ji} are unobserved characteristics described above and ε_i is the error term. We assume that y_i has a Poisson distribution and ε_i is distributed Gamma(α) so that

$$\Pr(y_i|\mathbf{x}_i, a_i, h_i, p_{ji}) = \frac{\Gamma(y_i + \psi)}{\Gamma(\psi)\Gamma(y_i + 1)} \left(\frac{\psi}{\mu_i + \psi}\right)^{\psi} \left(\frac{\mu_i}{\mu_i + \psi}\right)^{y_i} \equiv \mathbf{g}(.), \tag{7}$$

where $\mu_i = \exp\left(\mathbf{x}_i'\boldsymbol{\beta} + \sum_{j=1}^{4} \gamma_j d_{ji} + \sum_{j=1}^{4} \{\lambda_{aj} a_i + \lambda_{hj} h_i + \lambda_p p_{ji}\}\right)$ is the mean component of utilization and $\psi \equiv 1/\alpha$, which is the negative binomial model (NB-2). Note that when $\alpha \to 0$, the NB-2 specializes to the Poisson.

In our empirical implementation, we combine the three unobserved covariates for each plan choice into one latent factors, l_{ji}, which enters both the insurance choice (4) and the utilization (6) equations so that

$$\Pr[d_{ji} = 1|\mathbf{z}_i, a_i, h_i, p_{ji}] = \Pr[d_{ji} = 1|\mathbf{z}_i, l_{ji}] = \mathbf{f}(\mathbf{z}_i'\alpha_j + \delta_j l_{ji}) \tag{8}$$

and

$$\Pr(y_i|\mathbf{x}_i, a_i, h_i, p_{ji}) = \Pr(y_i|\mathbf{x}_i, l_{ji}) = \mathbf{g}(\mathbf{x}_i'\boldsymbol{\beta} + \sum\nolimits_{j=1}^{4} \gamma_j d_{ji} + \sum\nolimits_{j=1}^{4} \lambda_j l_{ji}), \tag{9}$$

Under these assumptions, the joint distribution of selection and outcome variables, conditional on the common latent factors, can be written as

$$\begin{aligned}\Pr(Y_i &= y_i, d_{ji} = 1|\mathbf{x}_i, \mathbf{z}_i, l_{ji}) = \mathbf{f}(\mathbf{z}_i'\boldsymbol{\alpha}_j + \delta_j l_{ji}) \\ &\times \mathbf{g}(\mathbf{x}_i'\boldsymbol{\beta} + \sum\nolimits_{j=1}^{4} \gamma_j d_{ji} + \sum\nolimits_{j=1}^{4} \lambda_j l_{ji})\end{aligned} \tag{10}$$

and, conditional on l_{ji} the log likelihood function for the model can be formed in the standard way. The l_{ji} are unknown, however, but can be integrated out of the log likelihood using simulation-based estimation. Specifically, assume that the l_{ji} are independently distributed with densities $\mathbf{h}_j$. Then the likelihood function for the joint model is

$$\begin{aligned}L(y_i, d_{ji}|\mathbf{x}_i, \mathbf{z}_i, l_{ji}) &= \prod_{i=1}^{N} \int \Big[\mathbf{f}(\mathbf{z}_i'\boldsymbol{\alpha}_j + \delta_j l_{ji}) \\ &\times \mathbf{g}(\mathbf{x}_i'\boldsymbol{\beta} + \sum\nolimits_{j=1}^{4} \gamma_j d_{ji} + \sum\nolimits_{j=1}^{4} \lambda_j l_{ji})\Big] \mathbf{h}_j(l_{ji}) dl_{ji} \\ &\approx \prod_{i=1}^{N} \frac{1}{S} \left[\sum_{s=1}^{S} \mathbf{f}(\mathbf{z}_i'\boldsymbol{\alpha}_j + \delta_j \widetilde{l}_{ji}) \right. \\ &\left. \times \mathbf{g}(\mathbf{x}_i'\boldsymbol{\beta} + \sum\nolimits_{j=1}^{4} \gamma_j d_{ji} + \sum\nolimits_{j=1}^{4} \lambda_j \widetilde{l}_{ji})\right]\end{aligned} \tag{11}$$

where $\widetilde{l}_{ji}$ are draws of l_{ji} from $\mathbf{h}_j$. The logarithm of this simulated likelihood is maximized using a quasi-Newton algorithm requiring only first derivatives.

The maximum simulated likelihood (MSL) estimator is consistent and asymptotically normal (Gouriéroux and Monfort, 1996). In univariate cases, a small number of random draws S is sufficient to reduce the simulation error to acceptable levels. However, previous experience suggests that many more draws would be required in multidimensional cases with endogenous regressors to achieve a similar level of accuracy. We use $S = 1000$ quasi-random draws based on Halton sequences to speed up convergence of the expectation (Bhat, 2001; Train, 2002, Deb and Trivedi, 2003).

In addition to the normalizations required for identification of the multinomial logit model, a normalization is required on either λ_j or δ_j because otherwise the variances of the multinomial logit choice equations are not identified. We assume $\delta_j = 1$ for each j and estimate values of λ_j. In addition, since $\delta_0 = 0$ and $\boldsymbol{\alpha}_0 = 0$ are required for normalization in the multinomial logit model, we assume $l_{0i} = 0$ without loss of generality.[6]

5.1. Inference

The sampling design of the CTS implies that the observations are clustered within 60 geographically defined sites. Therefore, standard errors the MSL estimates of parameters are obtained using a robust, "sandwich" formula for the covariance matrix, adjusted for site-level clustering.

5.2. Calculating Marginal Effects of Restrictions

The econometric model described above does not directly provide estimates of marginal effects of plan restrictions on the use of services. However, it is possible to uncover the effects of plan restrictions in the following way. First, we calculate predicted utilization for specific plan bundles denoted by $\mu[B(.,.,.)|x]$; for example, $\mu[B(1,0,0)|x]$ is the expected utilization for the plans that have a network of providers, do not require signups and do pay for care received outside the network. Then, we calculate effects of plan restrictions using differences between appropriately chosen predictions. In the language of the potential outcome model (Holland, 1986), these are average treatment effects (ATE). Specifically,

$$\begin{aligned} ATE(r_1) &= \mu[B(1,0,0)|\mathbf{x}] - \mu[B(0,0,0)|\mathbf{x}]; \\ ATE(r_2) &= \mu[B(1,1,0)|\mathbf{x}] - \mu[B(1,0,0)|\mathbf{x}]; \\ ATE(r_3) &= \mu[B(1,1,1)|\mathbf{x}] - \mu[B(1,1,0)|\mathbf{x}]; \end{aligned} \tag{12}$$

all else held constant. So $ATE(r_1)$ is the difference between expected utilization by an individual in a plan with NETWORK=1 and a plan with NETWORK=0, with covariates and other restrictions of the two health plans being compared being held constant.

[6] See Deb and Trivedi (2003) for a detailed discussion of identification issues in such models.

Note, however, that the choice of values for the other restrictions is not unique. We have chosen plans with PCPSIGNUP=0 and NOOUTNET=0 because these restrictions in combination with NETWORK=0 or NETWORK=1 are relatively prevalent in our sample. The average treatment effects of PCPSIGNUP and NOOUTNET on utilization are constructed similarly, with values for the other restrictions chosen in each case to correspond with commonly observed bundles in our sample. Note that the ATE's are calculated under the assumption that every individual in the target population is potentially exposed to the treatment. Note also that since the receipt and nonreceipt of a treatment are mutually exclusive states for individual i, only one of the two measures is directly identified in the data for any given i; the unavailable measure is counterfactual.

The individual predictions and associated treatment effects vary by individual characteristics. To summarize these effects, we calculate the sample averages of individual ATE's. We calculate standard errors of these sample-average effects using a Monte Carlo method. In this procedure, parameters from the joint model are drawn randomly from a multivariate normal distribution with mean given by the MSL estimates and covariance given by the MSL, cluster-corrected, sandwich estimates of the covariance matrix of parameters. For each draw, the sample-average of individual ATE's are calculated and this process is repeated 500 times. The standard error is calculated as the sample standard deviation of the 500 estimates of ATE's.

6. Results

In this section we discuss the results from five jointly estimated models. First we discuss the insurance choice equations and then utilization.

6.1. Insurance Choice

The estimates of the insurance equations from each of the five joint models are, not surprisingly, very similar. So we present and discuss estimates from only one of these, that from the joint model of insurance and visits to the doctor. Parameter estimates from this model are presented in Table 5. Our results are generally consistent with the findings in the literature on determinants of health plan choices (see Scanlon, et al., 1997, for a review). We find that older individuals are less likely to choose plans with restrictions but that educated individuals are more likely to choose plans with restrictions relative to plans without any of the three restrictions. Minorities are also more likely to choose plans with restrictions. Relative to plans with no restrictions, women are less likely to be in POS-type plans ($B(1,0,1)$) and more likely to be in HMO-type plans ($B(1,1,1)$). We find that healthier individuals are less likely to choose plans with restrictions on provider access. This is contrary to popular belief and empirical findings, especially for the elderly, but are consistent with findings of Schaefer and Reschovsky (2002) using the same data. We emphasize that our findings are conditional on being employed at a firm and insured, not for the general population.

The plan choice equations contain four characteristics of employers that are excluded from the utilization equations. Individuals who work for large firms and in the government sector are less likely to be enrolled in plans with restrictions. When firms offer HMO plans, employees are more likely to choose that option, ceteris paribus, but when firms offer non-HMO plans, individuals are less likely to choose the most restrictive plans ($B(1,1,0)$ and $B(1,1,1)$). To check that there is no weak instruments problem, the employer characteristics instruments are tested for joint significance in the equations for health plan choice using the likelihood ratio (LR) statistic and are found to be statistically significant in each case, confirming that the instruments are suitable.

6.2. Health Care Services

The estimated coefficients from the utilization equations are given in Table 6. For comparison, parameter estimates from utilization equations estimated treating insurance status as exogenous are reported in Table 7. A number of the factor loadings (coefficients on the latent factors) are statistically significant and likelihood ratio tests show that they are jointly significant. For each of the five measures of utilization there is significant evidence of selection into plans on the basis of unobserved heterogeneity. Selection effects are reflected in changes in sign, significance and magnitudes of coefficients on the plan dummy variables in the utilization equations when the joint estimator is applied. For example, a positive and significant coefficient on $B(1,0,0)$ in the doctor visits equation assuming exogeneity becomes insignificant once endogeneity is taken into account. On the other hand, the coefficient for $B(1,0,0)$, which is insignificant in the exogenous model for other medical professional visits is negative and statistically significant. In addition, although it appears that individuals in $B(1,0,0)$ plans are less likely to use emergency rooms as compared to individuals in $B(0,0,0)$ plans when insurance is treated as exogenous, in fact they are more likely to use emergency room services.

The joint models for hospital stays are less robust, i.e., these results seem to be sensitive to choice of instruments, sample definitions, etc. Our investigations suggest this is because over 90 percent of the realizations for this variable are equal to zero, while most of the remaining are ones. Thus, there is insufficient variation in the dependent variable for reliable identification. Subject to these caveats, the coefficients on plan bundles are never significant in the exogenous model for hospital stays, but they are positive and significant in two cases once endogeneity is modeled.

Results for visits to physician and other medical professionals which show that individuals in restrictive plans have more visits are consistent with the greater roles of primary care providers in MCOs. These results are also consistent with the findings of Kemper, et al. (2002). We also find some evidence that individuals in plans with few restrictions (POS, PPO plans) have significantly more surgeries and visits to emergency rooms, and also probably more hospital stays. These are consistent with the fact that modern indemnity plans typically have much higher out-of-pocket prices than managed care plans.

6.3. Effects of Plan Restrictions

We now turn to the main objective of this paper, which is to evaluate the effects of specific network and gatekeeping restrictions of health plans on provider access on utilization of medical care services. In order to calculate these, we use the formulae for

ATE (equation 12) described earlier. The sample averages of these treatment effects and their standard errors are reported in Table 8. The top panel reports ATE's based on the joint model of insurance and utilization; the estimates in the lower panel assume exogeneity of plans.

With respect to visits to doctors and other medical professionals, the existence of provider networks has little impact. Individuals in plans with networks seek somewhat less care from other medical professionals. These results also indicate the importance of modeling endogeneity of health plan choices as, under exogeneity, the results show that individuals in plans with networks use more physician services. Individuals in plans that require signups with PCPs, as compared to plans that do not require signups, substantially more care from other medical professionals but receive about the same care from doctors, ceteris paribus. The results are consistent with the view that plans with PCPs encourage different practice styles and referral patterns, encouraging care from less expensive non-physician medical practitioners whenever possible. Note that the finding for MDs is consistent with Escarce, et al. (2002), who also find no difference between the plan with a PCP requirement and another without in terms of care received from physicians, although the mix of PCP / specialist visits will vary. Individuals in plans that do not pay for out-of-network services receive substantially more care from physicians (1.4 more visits on average) and from other medical professionals (0.08 more visits on a "base" of 0.26, the sample average), ceteris paribus. Why do enrollees in the restrictive plan have more office-based visits? One reason is that out-of-pocket prices for office-based visits are lower in "closed" plans as compared to "open" plans. Second, such plans often limit the number of services per referral: limiting the number of services per referral forces patients to have more visits.

We find no effect of networks on the number of surgeries but that signups and out-of-network payment conditions do affect the number of surgeries significantly. Those in plans with required signups with PCPs have more surgeries (0.12 more compared to the sample average of 0.18) compared to those in plans without required signups. This is consistent with the view that "new" medical conditions are often diagnosed during routine exams with the PCP, which might remain undiagnosed when individuals do not have a regular provider of primary care. On the other hand, individuals in plans that do not pay for out-of-network services have substantially fewer surgeries. Here, the difference is likely due to the reduction of elective, and perhaps unnecessary, surgical procedures.

The results imply a substitution effect in use of emergency room services. Individuals in plans with networks and those that do not pay for out-of-network services are much more likely to receive emergency room treatment. This is consistent with the fact that it is harder to receive "after-hours" treatment in office settings in "closed" plans in which patients are often directed to emergency rooms as the primary source of "after-hours" care. The effect is especially large for plans that do not pay for out-of-network services as compared to plans that do. In such plans it is cheaper to receive care in an emergency room after-hours than care at the office of an out-of-network provider. On the other hand, individuals in plans that require signups with PCPs receive much less treatment in emergency room settings than their counterparts in plans that do not require signups. With regular checkups and primary care encouraged by PCPs, this result is completely intuitive. Note, however, that when exogeneity of plan choices is assumed, there is no significant difference between plans with PCPs and those without. Again, this points to the importance of accounting for endogeneity of plan choice.

As our models for hospital stays are less robust, the relative effects of plan restrictions on hospital stays should be interpreted with some caution. Subject to this caveat, we find significant evidence that individuals in plans with networks and those that require signups have more hospital stays. Again, this could be due to increased likelihood of disease detection for individuals in such plans. However, we do find that individuals in plans which do not pay for out-of-network services have significantly and substantially fewer hospital stays. A significant portion of the "excess" hospitalizations may be for elective surgical procedures, an explanation that is consistent with our findings for the number of surgeries.

In a few cases, the magnitudes of the sample averages of the ATE's are, perhaps, too large to be plausible. The sample-averages are "large" because the distributions of ATE's in the sample are skewed to the right in every case. These are shown in Figure 2. Consequently, the averages of the treatment effects are the largest of the commonly used measures of central tendency of the distribution of treatment effects. Sample medians and modes are smaller in each case.

6.4. Effects of Other Covariates

We find that statistical inferences about impact of exogenous covariates on utilization are not sensitive to the choice of the estimator. The results in Table 6 based on the joint model of treatments and outcome are similar to those in Table 7 that assumes exogeneity of insurance choice. Women have more visits to physicians and non-physician medical practitioners than men. They also have more surgeries and hospital stays than men but have similar numbers of emergency room visits. Older individuals receive more physician care, more surgeries and have more hospital stays but fewer emergency room visits. People with more education and income have more visits to the doctor. In addition, those with greater incomes also have more surgeries. Blacks and Hispanics have fewer surgeries and Hispanics fewer physician visits but blacks have more emergency room visits. Finally, physical and mental health status have large and expected effects. Persons in poorer health utilize more of each type of medical service.

6.5. Threats to Validity

Although our results are expected to be generally robust to computational issues and choices such as starting values, distributions of latent factors and the possibility of multiple optima, there are other substantive threats to the validity of our results that deserve discussion.

First, although we have modeled three important attributes of insurance plans, they are not exhaustive, i.e., plans have other financial and non-financial attributes. The omission of financial attributes (prices) is clearly important. As with most surveys, the CTS has information on out of pocket prices only for the plan chosen by the person, not on all available plans, so modeling or controlling for prices is not straightforward. However, if out-of-pocket prices of services are correlated with the attributes we have modeled (as pointed out by Kemper, et al., 2002), we cannot identify a "pure" restriction effect; instead we identify a restriction effect "contaminated" by a price effect.[7] In order to shed light on the possible extent of contamination, we calculated price differences between plans with each of the restrictions. Among plans with copayments, plans with a SIGNUP restriction have a 78 cent lower copayment per visit while plans with a NOOUTNET restriction have $1.32 lower copayment. The difference in copayment between plans with a NETWORK restriction and those without is small and statistically insignificant. Among plans with coinsurance, plans with NETWORK and SIGNUP restrictions have 0.67 and 0.92 percentage point lower coinsurance rates, while the difference in coinsurance rates is statistically insignificant for NOOUTNET. Using price elasticities of demand for health care services obtained from the RAND Health Insurance Experiment as a guide (Newhouse, et al. 1993), we tentatively conclude that our substantive findings cannot be explained away by price differences.

A second source of misspecification is in our choice of functional forms, especially as it relates to covariates. If our specification of covariates is not sufficiently rich, a finding of selection might simply be due to omitted nonlinearities. In preliminary analyses, we explored a variety of quadratic and interaction effects of covariates (including quadratic terms for AGE, FAMSIZE and INCOME and interactions of covariates with gender and minority status). None of these nonlinear effects was found to be consistently significant across specifications, in part because we have restricted our sample to a relatively homogeneous group. Therefore for conciseness, we report parameter estimates from a model with no nonlinear effects of covariates.

Finally, our instrumental variables are not uncontroversial. First, one might argue

[7] We thank Jim Reschovsky for highlighting this possibility.

that characteristics of the place of employment are correlated with unobserved health status in a way that makes these variables have direct effects on utilization, after controlling for observed health status and other covariates. Second, characteristics of the place of employment might be correlated with out-of-pocket prices for medical care. One expects out-of-pocket prices to affect utilization so for the characteristics of the place of employment to be valid instruments, they cannot be substantially correlated with out-of-pocket prices for medical care after controlling for exogenous characteristics of the individual. There is no formal way to test for the validity of the instruments in our nonlinear framework so we calculated Hansen's J-statistic for overidentification in a number of linear specifications of plan restrictions for each of the five outcomes. Of 16 such regressions, the J-statistic was never significant at 1 percent, only once at 5 percent and a majority of times, the p-value was greater than 0.7. We conclude that characteristics of the place of employment are reasonable instruments, at least for the sample of employees we have conditioned our analysis on.

7. Conclusion

Modeling self-selection into treatment in nonlinear limited dependent variable models is a technically difficult task when the treatment is multinomial. We have used computer intensive MSL methods to jointly model the choice of gatekeeper and network attributes of health insurance plans and health care utilization respecting the multinomial nature of health plan choice, the discreteness of utilization, and the possibility of self-selection into insurance plans. Our results show significant evidence of selection into managed care plans.

We find that enrollees in plans with networks of physicians have fewer office-based visits, both to physicians and other medical professionals, but more emergency room visits. Plans with networks, all else equal, successfully manage to reduce the amount of office-based care, but encourage the use of emergency rooms as sources of "after-hours" care. Individuals in plans that require signups with a PCP have more visits to non-physician providers of care, more surgeries and hospital stays but substantially fewer emergency room visits. Taken together, these findings are consistent with the view that regular visits to PCPs are often the source of diagnoses of “new” medical conditions that require surgical or hospital intervention. On the other hand, having such a regular source of care also reduces care received in emergency rooms. Finally, enrollees of plans that do not pay for out-of-network services have more office-based and emergency room visits, but less surgeries and hospitalizations. These findings are consistent with the view that such “closed” plans encourage substitution between office-based care and more expensive surgical and hospital care.

A more general model than ours would recognize the possibility of selection on supply side. That is, PCPs with different referral styles may select into different MCOs. Whether this type of selection reinforces or negates selection based on unobserved user characteristics is an open and difficult question. Our econometric model focuses on characteristics and behavior of the consumer, but those of health plan designers and providers are not modeled, but may be important. Further, additional information about plan characteristics such as benefit features and premiums can improve empirical modeling. Incorporating information on out-of-pocket prices of health care services is also clearly important. Both data and modeling issues along these dimensions are challenging, but deserving of emphasis in future research.

References

Amemiya, T. (1985), *Advanced Econometrics*, Cambridge: Harvard University Press.

Angrist, J.D. (2001), "Estimation of Limited Dependent Variable Models with Dummy Endogenous Regressors: Simple Strategies for Empirical Practice: Reply", *Journal of Business and Economic Statistics*, 19, 27-28.

Barringer M. W. and O.S. Mitchell (1994), "Workers' Preferences Among Company Provided Health Insurance Plans", *Industrial and Labor Relations Review*, 48, 141-152.

Bhat, C.R. (2001) "Quasi-random Maximum Simulated Likelihood Estimation of the Mixed Multinomial Logit Model", *Transportation Research: Part B,* 35, 677-693.

Cameron, A.C., P.K. Trivedi, F. Milne and J. Piggott (1988), "A Microeconometric Model of the Demand for Health Care and Health Insurance in Australia", *Review of Economic Studies*, 55, 85-106.

Cardon, J.H. and I. Hendel (2001), "Asymmetric Information in Health Insurance: Evidence from the National Medical Expenditure Survey", *RAND Journal of Economics*, 32, 408-427.

Center for Studying Health System Change (2000), "Community Tracking Study Household Survey, 1996-1997, and Followback Survey, 1997-1998, Washington D.C.

Christensen, S. and J. Shinogle (1997), "Effects of Supplemental Coverage on Use of Services by Medicare Enrollees", *Health Care Financing Review,* 19, 5-17.

Cunningham, P.J., C. Denk and M. Sinclair (2001), "Do Consumers Know How Their Health Plan Works?", *Health Affairs*, 20, 159-166.

Deb, P. and P.K. Trivedi (2003), "Specification and Simulated Likelihood Estimation of a Non-normal Treatment-Outcome Model with Selection: Application to Health Care Utilization", *Working Paper.*

Escarce, J.J., K. Kapur, G.F. Joyce and K.A. Van Vorst (2002), “Medical Care Expenditures Under Gatekeeper and Point-of-service Arrangements”, *Health Services Research*, 36, 1037-1057.

Feldman R., M. Finch, B. Dowd and S. Cassou (1989), “The Demand for Employment-based Health Insurance Plans”, *Journal of Human Resources*, 24, 115-142.

Glied, S. (2000), “Managed Care”, Chapter 13 in Culyer, A.J. and J.P. Newhouse, Editors, *Handbook of Health Economics,* Vol 1A, 707-745.

Gold, M. R., R. Hurley, T. Lake, T. Ensor, and R. Berenson (1995), “A National Survey of the Arrangements Managed-Care Plans Make with Physicians”, *New England Journal of Medicine*, 333, 1678-1683.

Goldman, D.P. (1995), “Managed Care as a Public Cost-Containment Mechanism”, *Rand Journal of Economics*, 26, 277-95

Goldman, D.P., S.D. Hosek, L.S. Dixon, E.M. Sloss (1995), “The Effects of Benefit Design and Managed Care on Health Care Costs”, *Journal of Health Economics*, 14, 401-18.

Gorman, W.M. (1980), “A Possible Procedure for Analysing Quality Differentials in the Egg Market", *Review of Economic Studies*, 47, 843-856.

Gouriéroux, C. and A. Monfort (1996), *Simulation Based Econometrics Methods*, New York: Oxford University Press.

Greene, W.H. (2002), *Econometric Analysis Fifth Edition,* Prentice Hall.

Gruber, J. (2000), “Health Insurance and Labor Market”, *Handbooks of Health Economics Vol. 1A*, Edited by Culyer, A. J. and J.P. Newhouse. Amsterdam: Elsevier.

Johnson, R.W. and S. Crystal (2000), “Uninsured Status and Out-of-pocket Costs at Midlife”, *Health Services Research*, 35, 911-932.

Kemper, P., H.T. Tu, J.D. Reschovsky, E. Schaefer (2002) "Insurance Product Design and Its Effects: Trade-Offs Along the Managed Care Continuum", *Inquiry*, 39, 101-117.

Lancaster, K. (1966), "A New Approach to Consumer Theory", *Journal of Political Economy,* 74, 132-157.

Lubalin, J.S., L.D. Harris-Kojetin (1999), "What Do Consumers Want and Need to Know in Making Health Care Choices", *Medical Care Research Review,* 56, 67-102.

Mello, M.M., S.C. Stearns, E.C. Norton (2002), "Do Medicare HMOs Still Reducatione Health Services Use After Controlling for Selection Bias?", *Health Economics,* 11, 323-340.

Miller, R.H. and H.S. Luft (1994), "Managed Care Plan Performance Since 1980", *Journal of American Medical Association*, 271, 1512-1519.

Newhouse, J.P. and the Insurance Experiment Group (1993), *Free for all? Lessons from the RAND Health Insurance Experiment*, Cambridge and London: Harvard University Press.

Olson, C. (2002), "Do Workers Accept Lower Wages in Exchange for Health Benefits", *Journal of Labor Economics*, 20, S91-S114.

Pauly, M., and S. Nicholson (1999), "Adverse Consequences of Adverse Selection", *Journal of Health Politics, Policy and Law*, 24, 921–930.

Reschovsky, J. D., J.L. Hargraves and A.F. Smith (2002), "Consumer Beliefs and Health Plan Performance: It's Not Whether You Are in an HMO but Whether You Think You Are, *Journal of Health Politics, Policy and Law*, 27, 353-377.

Scanlon, D. P., M. Chernew and J. R. Lave (1997), "Consumer Health Plan Choice: Current Knowledge and Future Directions", *Annual Review of Public Health*, 18, 507-528.

Schaefer, E. and J. D. Reschovsky (2002), "Are HMO Enrollees Healthier Than Others? Results From the Community Tracking Study", *Health Affairs*, 21, 239-258.

Train, K. (2002), *Discrete Choice Methods with Simulation,* New York: Cambridge University Press.

Tu, H.T., P. Kemper, and H.J. Wong (1999), "Do HMOs Make a Difference? Use of Health Services", *Inquiry*, 36, 400-410.

Vella, F. and M. Verbeek (1999), "Estimating and Interpreting Models with Endogenous Treatment Effects," *Journal of Business and Economic Statistics*, 17, 473-478.

Walker, J. and M. Ben-Akiva (2002), "Generalized Random Utility Model", *Mathematical Social Sciences*, 43, 303–343.

Table 1
Frequencies of Restrictions by Sample Definition

Sample	All	Employees
Sample size	20786	14885
NETWORK=1	88.0	88.9
PCPSIGNUP=1	48.4	50.8
NOOUTNET=1	36.5	38.0

Table 2
Frequencies of Bundles of Restrictions by Sample Definition

				Sample	
Bundle	NETWORK=	PCPSIGNUP=	NOOUTNET=	All	Employees
B(0,0,0)	0	0	0	12.0	11.1
B(1,0,0)	1	0	0	36.4	34.9
B(1,1,0)	1	1	0	15.1	16.0
B(1,1,1)	1	1	1	33.3	34.8
B(1,0,1)	1	0	1	3.2	3.2

Notes:
1 denotes the presence of the restriction while 0 denotes its absence.

Table 3
Descriptive Statistics for Measures of Utilization

		All		Employees	
Variable	Definition	Mean	Std. dev.	Mean	Std. dev.
Doctor	number of office-based physician visits	3.52	4.23	3.29	3.95
MedProf	number of other medical professional visits	0.26	0.78	0.25	0.75
Surgery	number of surgeries	0.18	0.51	0.17	0.48
ER	number of emergency room visits	0.26	0.65	0.24	0.62
Hospital	number of hospital discharges	0.11	0.45	0.08	0.37

Table 4
Demographic Characteristics by Sample Definition

		All		Employees	
Variable	Definition	Mean	Std. dev.	Mean	Std. dev.
Demographics					
AGE	age/10	4.02	1.17	3.94	1.10
FEMALE	=1 if female	0.53	0.50	0.50	0.50
BLACK	=1 if black	0.09	0.28	0.09	0.29
HISPANIC	=1 if Hispanic	0.06	0.24	0.06	0.25
MARRIED	=1 if married	0.73	0.45	0.68	0.46
INCOME	annual household income/10000	5.88	3.51	5.79	3.36
HIGRADX	years of education/10	1.41	0.24	1.41	0.23
Health status					
PHYSCLHLTH	SF-12 physical health score (0-100)/10	5.17	0.81	5.23	0.72
MENTALHLTH	SF-12 mental health score (0-100)/10	5.27	0.84	5.28	0.81
Employment					
GOVTJOB	=1 if government job	0.15	0.36	0.22	0.41
FIRMSZX	firm size indicator (1-6)	3.66	2.62	4.94	1.87
HMOOFR	=1 if HMO offered	0.57	0.50	0.68	0.47
NONHMOOFR	=1 if non-HMO offered	0.56	0.50	0.68	0.47

Table 5
Parameter Estimates From Plan-Bundle Choice Equations (System)

	B(1,0,0)		B(1,1,0)		B(1,1,0)		B(1,0,1)	
	Coef.	St. err.	Coef.	St. err.	Coef.	St. err.	Coef.	St. err.
FEMALE	-0.137*	0.049	0.057	0.057	0.144*	0.058	0.033	0.077
AGE	-0.087*	0.037	-0.080+	0.047	-0.152*	0.046	-0.014	0.063
MARRIED	-0.049	0.142	-0.003	0.142	0.025	0.144	-0.347	0.241
HIGHGDX	-0.013	0.147	0.634*	0.187	0.338*	0.175	0.155	0.388
NPERX	-0.006	0.044	-0.010	0.046	0.046	0.045	0.123*	0.067
INCOME	0.018	0.016	0.037*	0.019	0.002	0.018	0.028	0.031
BLACK	0.343+	0.182	0.585*	0.205	0.782*	0.203	0.500*	0.259
HISPANIC	0.214	0.321	0.618*	0.292	1.044*	0.321	1.651*	0.409
PHYSCLHLTH	-0.067*	0.034	-0.089	0.065	-0.091*	0.042	-0.081	0.063
MENTALHLTH	-0.059	0.046	-0.108*	0.041	-0.156*	0.038	-0.194*	0.076
HMOOFR	-0.171+	0.094	1.075*	0.095	1.819*	0.089	1.043*	0.199
NONHMOOFR	-0.135	0.117	-0.524*	0.101	-0.397*	0.095	-0.132	0.155
FIRMSIZX	-0.038	0.033	0.050	0.038	-0.067*	0.028	-0.054	0.054
GOVTJOB	0.139	0.179	-0.686*	0.280	-0.018*	0.221	0.243	0.281

Notes:

* indicates that the parameter is significantly different from zero at the 5 percent level.

+ indicates that the parameter is significantly different from zero at the 10 percent level.

Table 6
Parameter Estimates From Utilization Equations (System)

	Parameter Estimates									
	Doctor		MedProf		Surgery		ER		Hospital	
	Coef.	St. err.	Coef.	St. err.	Coef.	St. err.	Coef.	St. err.	Coef.	St. err.
FEMALE	0.512*	0.016	0.432*	0.056	0.273*	0.037	-0.086+	0.044	0.586*	0.071
AGE	0.026*	0.009	-0.111*	0.026	0.078*	0.025	-0.161*	0.020	0.052+	0.031
MARRIED	0.043+	0.025	-0.139+	0.074	-0.066	0.073	-0.229*	0.073	0.189*	0.088
HIGHGDX	0.249*	0.048	0.600*	0.191	0.156	0.120	-0.520*	0.100	-0.054	0.156
NPERX	-0.029*	0.009	-0.022	0.028	0.025	0.023	0.016	0.021	0.043+	0.026
INCOME	0.012*	0.003	-0.001	0.011	0.026*	0.006	-0.006	0.010	0.014	0.012
BLACK	-0.058	0.036	-0.136	0.094	-0.364*	0.083	0.283*	0.074	0.221+	0.116
HISPANIC	-0.154*	0.038	-0.062	0.140	-0.308*	0.108	0.039	0.100	0.096	0.136
PHYSCLHLTH	-0.407*	0.009	-0.400*	0.029	-0.358*	0.028	-0.502*	0.025	-0.548*	0.050
MENTALHLTH	-0.154*	0.012	-0.145*	0.023	-0.107*	0.022	-0.199*	0.019	-0.160*	0.036
B(1,0,0)	-0.022	0.093	-0.240+	0.125	0.216	0.187	0.500*	0.181	0.599*	0.228
B(1,1,0)	-0.027	0.078	0.127	0.106	0.797*	0.122	-0.342+	0.187	1.089*	0.188
B(1,1,1)	0.369*	0.115	0.421*	0.119	0.277	0.202	0.602*	0.106	-0.101	0.167
B(1,0,1)	0.617*	0.087	0.780*	0.166	-0.027	0.207	0.327	0.316	-0.247	0.193
λ[B(1,0,0)]	0.106	0.100	0.090*	0.044	-0.187	0.171	-0.700*	0.175	-0.706*	0.211
λ[B(1,1,0)]	0.118	0.081	-0.016	0.014	-0.972*	0.085	0.333+	0.195	-1.244*	0.108
λ[B(1,1,1)]	-0.312*	0.134	-0.092+	0.051	-0.279	0.176	-0.762*	0.144	0.209	0.157
λ[B(1,0,1)]	-0.723*	0.068	-0.009	0.007	-0.125	0.129	-0.139	0.274	0.239*	0.111

Notes:

* indicates that the parameter is significantly different from zero at the 5 percent level.

+ indicates that the parameter is significantly different from zero at the 10 percent level.

Table 7
Parameter Estimates From Utilization Equations (Exogenous Plan-Bundle Choice)

	Parameter Estimates									
	Doctor		MedProf		Surgery		ER		Hospital	
	Coef.	St. err.	Coef.	St. err.	Coef.	St. err.	Coef.	St. err.	Coef.	St. err.
FEMALE	0.468*	0.016	0.434*	0.056	0.263*	0.037	-0.069	0.043	0.482*	0.082
AGE	0.020*	0.009	-0.111*	0.025	0.071*	0.025	-0.169*	0.020	0.061+	0.033
MARRIED	0.014	0.027	-0.140+	0.073	-0.059	0.067	-0.234*	0.074	0.168+	0.087
HIGHGDX	0.219*	0.050	0.606*	0.192	0.183	0.116	-0.523*	0.098	-0.023	0.164
NPERX	-0.020*	0.010	-0.022	0.028	0.018	0.022	0.026	0.022	0.041	0.027
INCOME	0.010*	0.003	-0.001	0.011	0.030*	0.006	-0.011	0.010	0.013	0.012
BLACK	-0.038	0.034	-0.130	0.094	-0.346*	0.081	0.302*	0.073	0.128	0.114
HISPANIC	-0.077+	0.043	-0.034	0.140	-0.295*	0.101	0.066	0.091	0.011	0.140
PHYSCLHLTH	-0.399*	0.009	-0.401*	0.029	-0.360*	0.026	-0.470*	0.022	-0.531*	0.045
MENTALHLTH	-0.158*	0.012	-0.147*	0.023	-0.105*	0.022	-0.187*	0.019	-0.129*	0.039
B(1,0,0)	0.056+	0.034	-0.161	0.126	0.002	0.103	-0.117+	0.064	-0.021	0.142
B(1,1,0)	0.093*	0.042	0.130	0.105	-0.069	0.114	-0.111	0.068	0.010	0.152
B(1,1,1)	0.125*	0.037	0.367*	0.094	0.005	0.114	-0.048	0.076	-0.014	0.130
B(1,0,1)	-0.043	0.060	0.810*	0.161	-0.084	0.149	0.206+	0.120	0.092	0.188

Notes:

* indicates that the parameter is significantly different from zero at the 5 percent level.

+ indicates that the parameter is significantly different from zero at the 10 percent level.

Table 8
Sample Average of Individual Treatment Effects of Plan Restrictions

	Doctor		MedProf		Surgery		ER		Hospital	
	Marg.	St. Err.	Marg.	St. Err.	Marg.	St. Err.	Marg.	St. Err.	Marg.	St. Err.
	accounting for endogeneity of health plan choice									
NETWORK	-0.065	0.292	-0.046+	0.025	0.031	0.028	0.121*	0.055	0.055*	0.028
PCPSIGNUP	-0.013	0.203	0.076*	0.023	0.124*	0.050	-0.175*	0.042	0.078+	0.046
NOOUTNET	1.401*	0.523	0.084*	0.038	-0.114+	0.061	0.208*	0.078	-0.140*	0.031
	assuming exogeneity of health plan choice									
	Marg.	St. Err.	Marg.	St. Err.	Marg.	St. Err.	Marg.	St. Err.	Marg.	St. Err.
NETWORK	0.176+	0.099	-0.034	0.026	3e-4	0.016	-0.029+	0.015	-0.002	0.012
PCPSIGNUP	0.119	0.094	0.061*	0.021	-0.012	0.009	0.001	0.014	0.003	0.009
NOOUTNET	0.110	0.088	0.065*	0.026	0.012	0.009	0.015	0.014	-0.002	0.009

Notes:

* indicates that the parameter is significantly different from one at the 5 percent level.

+ indicates that the parameter is significantly different from one at the 10 percent level.

Figure 1: Schematic Representation of the Model

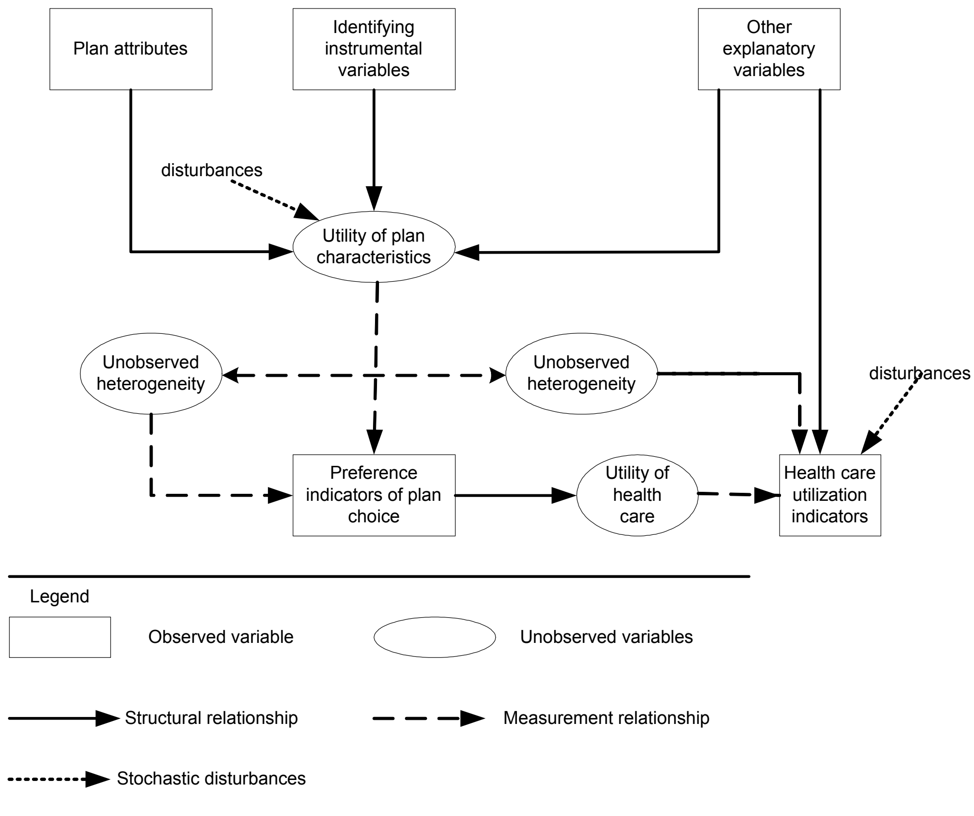
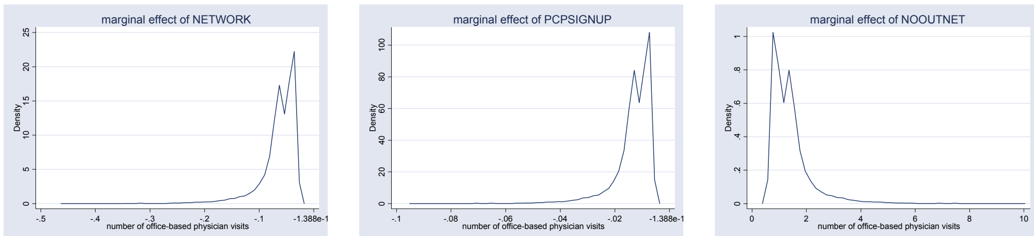
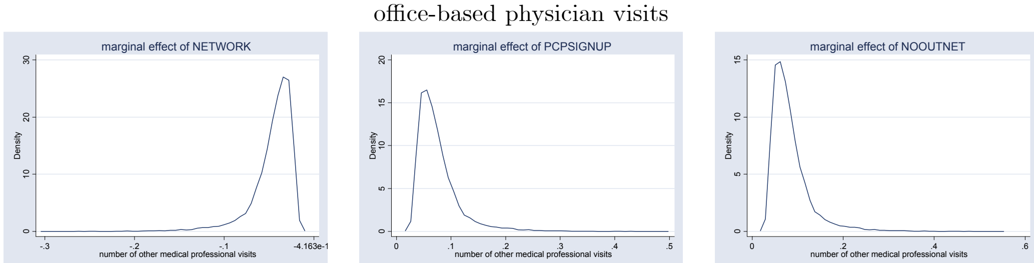


Figure 2: Kernel Densities of Individual Treatment Effects of Plan Restrictions

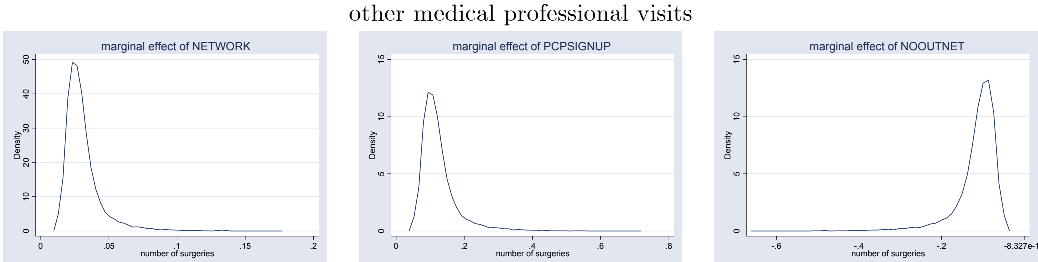
NETWORK PCPSIGNUP NOOUTNET



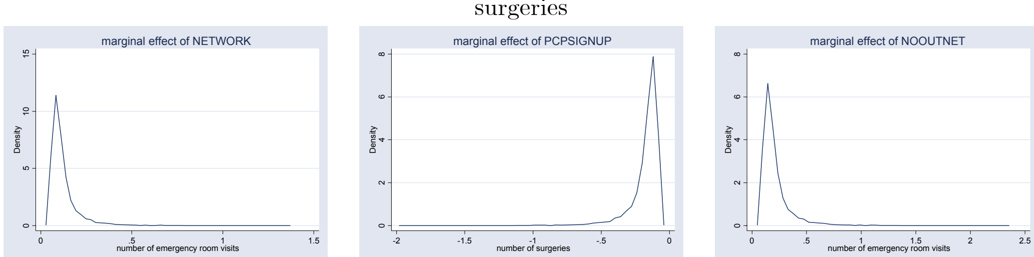
office-based physician visits



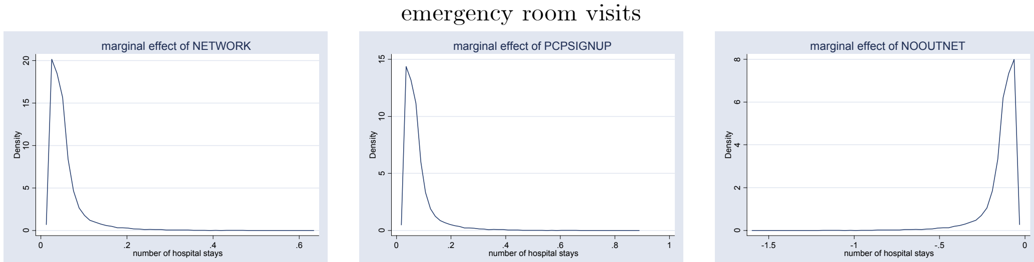
other medical professional visits



surgeries



emergency room visits



hospital stays